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Fuzzy logic-based prediction data for the CNC lathe

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ABSTRACT

Purpose: The research aims to predict the parameters between the cutting speed range correlated to the depth of cut for the CNC lathe.

Design/methodology/approach: The model predicts the cutting speed parameters carried out based on the data range between the depth of the cut and the cutting speed. That information has been derived from the machine tool handbook and expert engineer recommendations. The fuzzy logic-based methods were used to predict cutting speed parameters for three different materials: aluminium, machine steel, and stainless steel. The data range in each material was used to condition the membership function.

Findings: The result shows that the prediction cutting speed parameters are related to the range of the depth of the cut between 0.15 and 0.4 mm. It is observed that if the depth of the cut is very high, the cutting speed is lower. The information obtained is slightly different from the machine tool handbook. It can be used with the feed rate parameters to perform the machining process of the CNC lathes in the smart factory.

Research limitations/implications: Further research should focus on predicting surface roughness and tool wear in the turning.

Practical implications: The cutting speed selection has a significant impact on manufacturing. It affects production time, tool wear, cost, etc. Generally, the parameter has been derived from machining handbooks or machine tools textbooks, and some data is vague because it has only maximum and minimum. The data between ranges is unclear for operation. Executing production planning for new engineers was hard, which can affect manufacturing systems. Therefore, proper and precise cutting parameters are required.

Originality/value: General machine tool manuals often provide vague information on recommended parameters and only show the maximum and minimum values. In past research, it has only a determined parameters range for the experiment. The data between ranges is unclear for operation. In this research, the parameter prediction was performed between the cutting speed range related to the cutting depth, which is for use in the CNC lathe process.

Keywords: Fuzzy logic, CNC lathe, Prediction data, Smart factory

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METHODOLOGY OF RESEARCH, ANALYSIS AND MODELLING

1. Introduction

The machining process section is still essential in manufacturing, and production lead times must be short to keep pace with rapidly changing market demands. Therefore, proper machining process planning is required. Cutting speed selection has a significant impact on manufacturing, affecting production time. Generally, the data are derived from machining handbooks or machine tools textbooks, and some data are vague because they only have maximum and minimum. The data between ranges is unclear for operation. It was hard to process planning for the new engineer. The cutting speed parameter is also related to spindle speed. Usually, it can calculate the revolutions per minute (RPM) by equation. In this case, the engineers must spend more time solving for the optimum parameters. The equation of spindle speed is as follows:

$$V = \frac{\pi DN}{1000} \tag{1}$$

where N stands for revolution per minute (rpm), V is cutting speed (m/min), and D is the outer diameter of the workpiece.

In addition, the experts suggest that cutting speed in some case processes should be related to the depth of cut because it affects tool life, cost, product, power consumption, etc., which depends on each case of machining and the experience of the engineer process planning.

Fuzzy logic is well-known as a methodology to solve the problem of ambiguity and uncertainty, and it has a membership function range between 0 and 1 for assigning to each object. That was presented by Zadeh [1] in 1965. Such a method is of interest in development for use in the manufacturing processes, and Mamdani [2] has an experiment on linguistic synthesis with a fuzzy logic controller. The goal is to investigate how humans interact with the learning controller model in a factory setting. That used the concept of the fuzzy set A of U = u1, u2, …, un. That was denoted equation for control as follows:

$$A = \sum_{i=1}^{n} \mu_A \frac{(\mu_i)}{\mu_i} = \sum_i \mu_A (\mu_i) \tag{2}$$

where Σ stands for the union. The function formula corresponds to an OR of fuzzy subsets A and B. That was the union equation as follows:

$$A + B = \sum_i \mu_A (\mu_i) \vee \mu_B(\mu_i) \tag{3}$$

where ∨ stands for maximum. The function formula corresponds to AND of fuzzy subsets A and B. That was the intersection equation as follows:

$$A \cdot B = \sum_i \mu_A (\mu_i) \wedge \mu_B(\mu_i) \tag{4}$$

where ∧ stands for a minimum.

That "IF…Then" is a language the theory rule base for representing the relationship of fuzzy logic, which has also been successfully an alternative method to reasoning under ambiguity. It is also used to develop rule-based expert systems. This way was applied to predict machining solutions by many researchers, such as Ramesh [3], who studied a fuzzy logic model to predict cutting parameters when turning titanium alloys. Azmi [4] has designed a fuzzy logic model to predict tool performance during machining composite materials, which follows the means fuzzy inference system (FIS) of the Mamdani method. The machining condition consists of feed rate, cutting speed, and depth of cut. Maher [5] studied cutting force in end milling operations to predict surface roughness by a fuzzy methodology. Bobyr [6] used fuzzy logic computing to predict cutting force control, in which the input variable is the cutting force and diameter of the workpiece. Tseng [7] presented a prediction of surface roughness in machining operations. It has used the centroid method for the defuzzification result of the fuzzy system, which is a technique that calculates the average weighted by the equation as follows.

$$COA(A) = \frac{\sum_x \mu_A(x) \times x}{\sum_x \mu_A(x)} \tag{5}$$

Saranya [8] studied the selection of optimal cutting tools and process parameters for effective turning and milling operations, which used the adaptive neuro-fuzzy system to select suitable tools. Asadi [9] used the coupled models of adaptive neuro-fuzzy inference systems and interval type 2 fuzzy neural networks to predict mean values of cutting forces and average surface roughness (Ra) in milling aluminium alloys. Marani [10] studied cutting tool wear during a turning process for prediction by the fuzzy method. Hanachi [11] used a hybrid data-driven physics-based model fusion framework for tool wear prediction. Chiu [12] presented machining accuracy and surface quality for CNC machine tools, which have used adaptive neuro-fuzzy inference systems for prediction. Muhammad [13] analysed data from a Ti-based alloy's ultrasonic vibration-assisted turning and conventional turning to forecast the highest temperature, cutting forces, surface roughness, chip compression ratio, and shear angle using a fuzzy logic model. The model had two input variables - speed and depth of cut. In addition, Fuzzy logic is also used along with other methods to predict cutting parameters, such as the Taguchi approach to predict the optimal machining effectiveness for machining structural steel AISI 1015 [14] and reducing tool wear [15]. Alajmi [16] used an adaptive neuro-fuzzy inference system with quantum particle swarm optimisation to predict the surface roughness on turning stainless steel.

Furthermore, the Fuzzy logic model was used to predict other machining, such as material removal rate, tool wear rate, wear rate, and surface roughness of electrical discharge machining [17-19]. The fuzzy sets methods, such as fuzzy failure mode and effects analysis (fFMEA), are also used for production risk assessment. This solution avoids the uncertainty of FMEA, which allows risk calculation and prioritization in the case study of comparing and performing the risk evaluation of the Final Quality Control (FQC) process in the automotive industry [20,21].

Fuzzy logic methods are used in the research area for prediction, which depends on the reasoning of each case. Sometimes, it has been adapted to artificial intelligence or coupled with other methodologies to predict optimum parameters. The past research has only a determined parameter range for the experiment. It is the same as the information recommended in the machine tool manual. The data between the highest and lowest values is still vague. Thus, this research aims to predict only the parameters between the cutting speed range correlated to the depth of the cut. It gives new, in-depth information that can be used to plan factory production processes.

2. Methodology

The section has described a solution of fuzzy logic to the predictive parameter, which was based on the experience of experts in the factory. The parameter for prediction consisted of the depth of cut and cutting speed. The data range (max. and min.) for carry out in this paper is shown in Table 1. It is derived from the machine tools handbook [22]. The data was suggested for carbide tools for machining in the turning process. The materials for conducting consist of aluminium, machine steel (free machining carbon steel), and stainless steel. MATLAB (R2014a) software was used for calculation, and the central processing unit is Intel(R) Core (TM) i7-10750H CPU @ 2.60GHz run on Windows 10.

Table 1.
Parameter range of cutting speed and depth of cut

Depth of cut, mm	Cutting speed, m/min		
	aluminium	machine steel	stainless steel
0.15-0.4	215-305	215-305	115-150

2.1. Fuzzy approach

The prediction model of the cutting speed parameters is carried out based on the data range between the depth of the cut and the cutting speed. This was derived from the machine tool handbook and expert engineer recommendations. In the paper, the input is the depth of cut, and the output is the cutting speed for three materials: aluminium, machine steel, and stainless steel. The Mamdani method and technique of the centroid method were used for the defuzzification result of the fuzzy system. The fuzzy prediction model is shown in Figure 1.

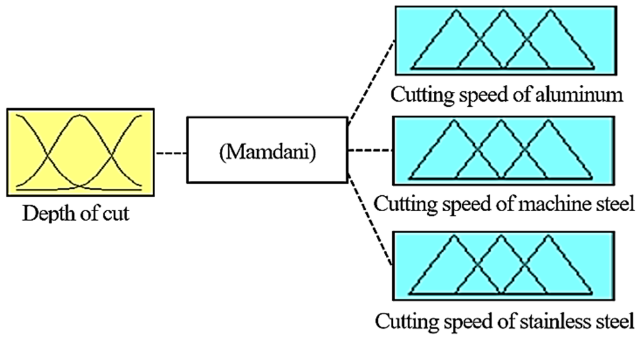

Fig. 1. Fuzzy prediction model

2.2. Fuzzy rules

Fuzzy rules are defined based on experts' experience in traditional turning processes, which states, "As the depth of cut increases, The cutting speed must be slower." It is a linguistic concept to form a fuzzy rule base. It consists of five rules. That has a group if-then control rule, as follows:

- Rule 1. If the depth of cut is very low (VL), then the cutting speed of aluminium, machine steel, and stainless steel is very high (VH);
- Rule 2. If the depth of cut is low (LW), then the cutting speed of aluminium, machine steel, and stainless steel is high (HI);
- Rule 3. If the depth of cut is medium (MD), then the cutting speed of aluminium, machine steel, and stainless steel is medium (MD);
- Rule 4. If the depth of cut is high (HI), then the cutting speed of aluminium, machine steel, and stainless steel is low (LW);
- Rule 5. If the depth of cut is very high (VH), then the cutting speed of aluminium, machine steel, and stainless steel is very low (VL).

2.3. Membership function for input and output of the fuzzy model

The fuzzy sets used triangular shapes to describe behaviours identified by the knowledge expertise. The membership function of the input parameter has a range of

0.15-0.4. That is shown in Figure 2. The linguistic synthesis with fuzzy logic has five levels consisting of very low (VL), low (LW), medium (MD), high (HI), and very high (VH). That is shown in abbreviations and expressions in Table 2.

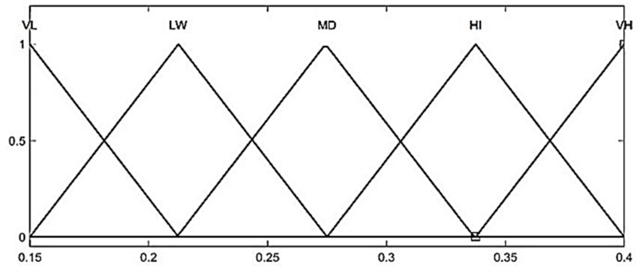

Fig. 2. Input membership function

In Figure 2, the input universe “depth of cut” should be partitioned according to the minimum and maximum values allowed to the control system. On this basis, the universe of depth of cut has been split in the range of (0.15-0.4). It is divided into five levels of input fuzzy sets. A value of 0.15 is assigned to a very low, and a value of 0.4 is assigned to a very high depth of cut.

Table 2.
Fuzzy expressions for input fuzzy sets

Abbreviation	Expressions (depth of cut)
VL	very low depth
LW	low depth
MD	medium depth
HI	high depth
VH	very high depth

The output membership function of the cutting speed parameter was divided into three materials: aluminium, machine steel, and stainless steel. The data range consists of 215-305, 215-305, and 115-150, respectively. It is shown in Figure 3. The linguistic synthesis of a fuzzy has five levels consisting of very low (VL), low (LW), medium (MD), high (HI), and very high (VH). That is shown in abbreviations and expressions in Table 3.

Table 3.
Fuzzy expressions for output fuzzy sets

Abbreviation	Expressions (cutting speed)
VL	very low speed
LW	low speed
MD	medium speed
HI	high speed
VH	very high speed

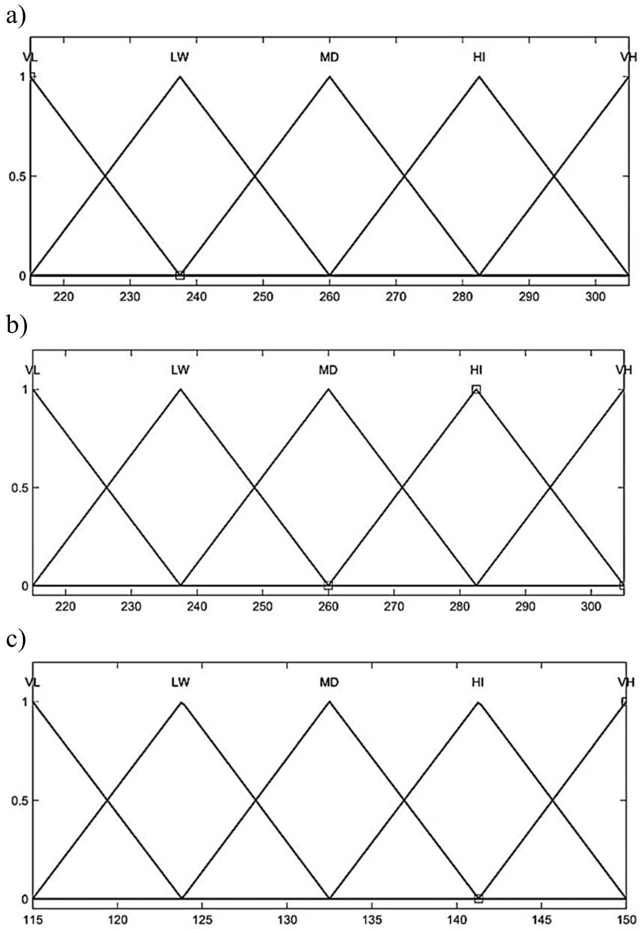

Fig. 3. Output membership function of cutting speed in each material: a) aluminium, b) machine steel, c) stainless steel

As shown in Figure 3, the "cutting speed" output universe must be partitioned based on the minimum and maximum values allowed by the control system. The output universe of aluminium and machine steel (as depicted in Fig. 3a and Fig. 3b) has been divided into five levels of output fuzzy sets within the range of (215-305). The cutting speeds of 215 and 305 are assigned to very low and very high, respectively. In Figure 3c, the universe of stainless steel has been split into a range of (115-150), with 115 representing very low and 150 representing very high cutting speeds.

3. Results and discussion

The fuzzy predicted cutting speed for depth of cut between range 0.15-0.4 mm. That range is taken from the machine tool handbook. It is recommended as the default for applications involving the cutting speed of single-point carbide tools in turning processes. The results are shown in Table 4, and the prediction graph of aluminium and machine steel is shown in Figure 4. The prediction graph of stainless steel is shown in Figure 5. The depth of cut data was represented on the x-axis, fuzzy cutting speed prediction was represented on the y-axis. The result indicates that if the depth of cut is very much, the cutting speed is less. That has a slightly different parameter from the machine tool handbook. It is shown in Table 5.

Table 4.
The fuzzy predicted cutting speed for depth of cut between range 0.15-0.4 mm

Depth of cut, mm	Fuzzy cutting speed, m/min		
	aluminium	machine steel	stainless steel
0.15	298	298	147
0.16	292	292	145
0.17	288	288	143
0.18	286	286	142
0.19	284	284	142
0.20	283	283	141
0.21	283	283	141
0.22	279	279	140
0.23	275	275	138
0.24	272	272	137
0.25	269	269	136
0.26	266	266	135
0.27	262	262	133
0.28	258	258	132
0.29	254	254	130
0.30	250	250	129
0.31	248	248	128
0.32	244	244	126
0.33	241	241	125
0.34	237	237	124
0.35	237	237	124
0.36	236	236	123
0.37	234	234	123
0.38	232	232	122
0.39	228	228	120
0.40	222	222	118

A comparison of data cutting speed between the machine tool handbook and fuzzy prediction is shown in Table 5. It is shown that the prediction value does not have much error when compared to the maximum and minimum parameters. It has an average error of 2.61 per cent, which can be used with the feed rate parameter to perform machining planning. It has been investigated by turning experiments with the CNC lathe and conventional turning. The results were satisfactory, which were not shown in the article.

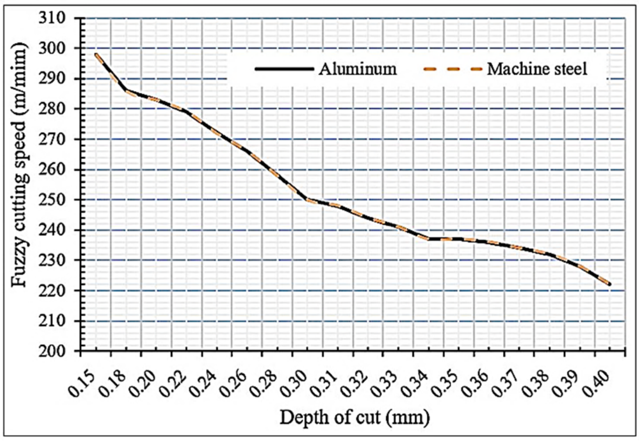

Fig. 4. The prediction graph of aluminium and machine steel

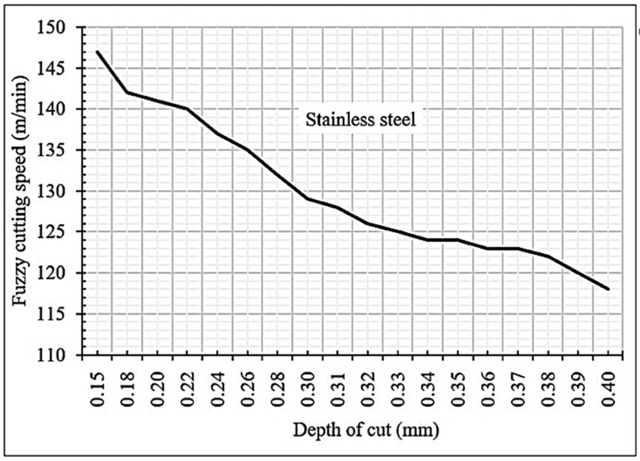

Fig. 5. The prediction graph of the stainless steel membership function

Table 5.
The data compared cutting speed in the depth of cut (min. and max.) range of 0.15-0.4 mm

Material	Depth of cut, mm	Cutting speed, m/min		
		machine tool handbook	fuzzy predict	error, %
aluminium	0.15	305	298	2.29
	0.4	215	222	3.25
machine steel	0.15	305	298	2.29
	0.4	215	222	3.25
stainless steel	0.15	150	147	2.00
	0.4	115	118	2.61

4. Conclusions

The fuzzy logic model predicted parameters between the data range (maximum and minimum) of the depth of cut and cutting speed. It is used in three materials: aluminium, machine steel (free machining carbon steel), and stainless steel in the CNC lathe process. It has been concluded that the fuzzy prediction cutting speed is similar to data from the machine tool handbook, which has an average error of 2.61 per cent. That data is shown in the result table, and the fuzzy cutting speed graph is shown in every data range. The information can be adapted for industrial applications. Future work will be focused on predicting surface roughness and tool wear in the turning process.

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Authors contribution

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [Siridech Kunhirunbawon, Ph.D.], [Narisara Suwichien], [Tanakorn Jantarasricha, Ph.D.], and [Suthep Butdee, Ph.D.]. The first draft of the manuscript was written by [Siridech Kunhirunbawon, Ph.D.] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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